Wind Power Forecasting: A Review of Statistical Models

Wind Power Forecasting

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Abstract

Several wind power or wind speed forecasting methods have been reported in the literature over the past few years. A brief overview and comparison of all these techniques is the main focus of the present work. This paper provides insight on the foremost forecasting techniques, associated with wind power and speed, based on numeric weather prediction (NWP), statistical approaches, ARIMA models, artificial neural network (ANN), grey models, data mining models and hybrid techniques over different time-scales. The various wind power forecasting techniques have been categorized into following three major classes: (i) Physical models, (ii) Statistical models, and (iii) Hybrid models. It has been observed that forecasting accuracy of different models vary due to different types of terrain and wind turbulence at the different wind farms. Based on the assessment of wind power forecasting techniques, further direction for additional research and application is proposed.

Keywords

Wind Power Forecasting; Numeric Weather Prediction; Physical And Statistical Models

Introduction

Wind generation has been one of the fastest growing energy technologies in the world for the past decade. The world wind energy sector has an installed capacity of 200 GW up to 2010 [1]. The main characteristic of this power is that it varies over time, mainly under the influence of meteorological fluctuations. The variations occur on all time scales: seconds, minutes, hours, days, months, seasons and years. Understanding these variations and their predictability is of key importance for the integration of wind generation in the power system. As the amount of generated wind power has reached high levels in the world, there has been a continuous improvement of wind power forecasting models over the last decade [2]. A number of wind power forecasting providers have emerged and there is competition to provide the best forecasts to the electric power industry. These forecasts are used by several different groups of users namely generation companies and utilities, market analysts and traders, and electricity market operators. Forecasting models vary widely in their time horizons, factors determining actual outcomes, types of data patterns and many other aspects. From milliseconds up to a few minutes, forecasts can be used for the turbine active control. For 48-72 hours, forecasts are used for the power system management or energy trading. For longer time scales (up to 5-7 days ahead), forecasts may be used for planning the maintenance of wind farms or conventional power plants or transmission lines.

Numerous methods have been proposed by different researchers based on artificial neural networks (ANN) [3-6], fuzzy models [7-8], support vector machine (SVM) [9], density forecasts from weather ensemble predictions [10], wavelets [11] and fractional-ARIMA (*f*-ARIMA) [12] *etc.* A review of these forecasting technologies is a difficult yet an important task. Although some attempts have been made in this direction [13-14], yet the authors of this work feel an updating of the review of this dynamic field is desired at this point of time for further scholarly research. In order to do so, a review of 42 papers has been done. The papers have been categorized based on the methodology involved and put in a chronological order. Rest of the paper is organized as follows: In Section 2, characteristics of the wind time series is given. In Section 3, various wind-forecasting models and their features have been explained. Discussion and key issues are given in Section 4. Section 5 concludes the review.

Characteristics of Wind Time Series

A time series is a chronological sequence of observations of a particular variable. If a time series has a regular pattern, then a value of the series should

be a function of previous values. The wind speed time series is characterized by seasonal as well as diurnal effects. The diurnal effect corresponds to possible daily periodic behavior of wind, which depend on the specific geographic characteristics of the respective region. The three timescales that concern the system operator for day ahead scheduling are minute-to-minute, intra hour and hour-to-hour [15]. These variations can be forecasted to some extent by method based on time series analysis.

The wind power dataset during year 2008 for the Ontario (http://www.ieso.ca) has been analyzed to identify the characteristics of wind power at a yearly, monthly and hourly timescales. A wind speed time series, such as in Fig. 1, Fig. 2 and Fig. 3 possesses characteristics such as time varying mean and variance, which are typical characteristics of a non-stationary time series. No typical patterns can be directly found from the signal and the prediction for such kinds of data requires special care.

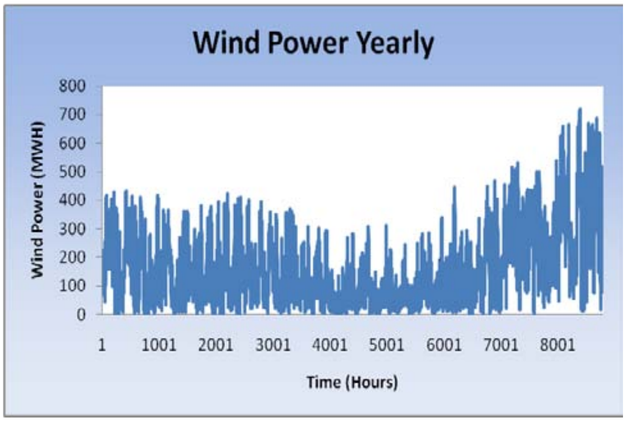

FIG. 1 YEARLY PATTERN OF WIND POWER IN ONTARIO

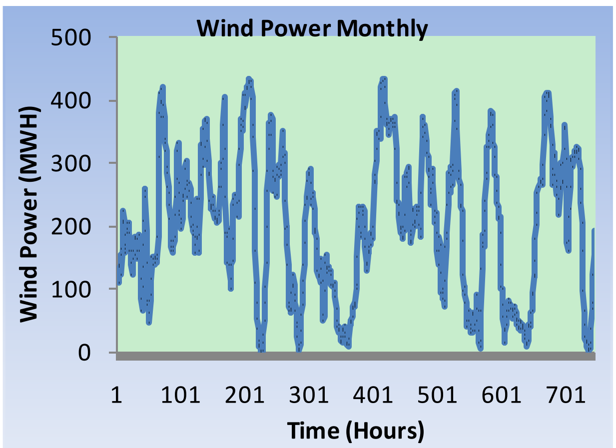

FIG. 2 MONTHLY PATTERN OF WIND POWER IN ONTARIO

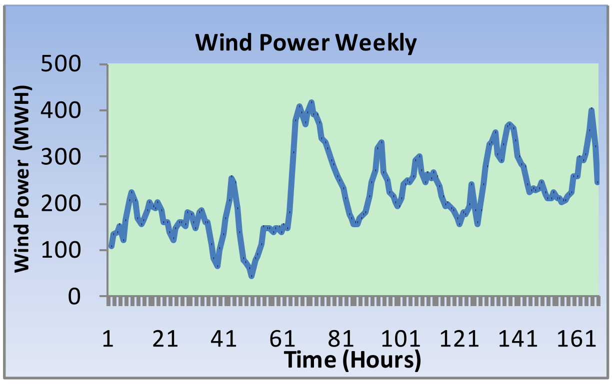

FIG. 3 WEEKLY PATTERN OF WIND POWER IN ONTARIO

Wind Power Forecasting Models

A wind power forecasting model uses input data from different sources like numerical weather prediction (NWPs) models, supervisory control and data acquisition (SCADA) system describing the real-time state of the wind power plants and local real-time meteorological conditions. Based on the methodology, the wind-forecasting models can be classified in the following three categories: (i) physical model, (ii) statistical model, and (iii) hybrid model.

Physical Models

Physical model describes the physical relationship between wind speed, atmospheric conditions, local topography and the output from the wind power plant. This model consists of several sub models, which together deliver the translation from the wind forecast at a certain grid point and model level to power forecast at the considered site and at turbine hub height [16]. This consists of two main steps: (i) downscaling, and (ii) conversion to power. The downscaling step scales the wind speed and direction to the turbine hub's height and consists of finding the best-performing NWPs level. The main idea is to refine the NWPs by using physical considerations about the terrain such as the roughness, orography and obstacles and by modeling the local wind profile. The two main alternatives to do so are: a) combine the modeling of the wind profile and the geotropic drag law in order to obtain surface winds [16], and b) use a computational fluid dynamics (CFD) code that enables accurate computation of the wind field that the farm will see, considering a full description of the terrain. The conversion-to-power step consists of converting the wind speed to power by using a power curve. For an NWP model, statistical relations between model-

forecast variables and observed weather variables are used for correction of model-forecast variables.

Statistical Model

These models form the second class of wind-forecasting models. They do not aim at describing the physical steps involved in the wind power conversion process; but, estimate a statistical relationship between relevant input data and the wind power generation. It involves direct transformation of the input variables into wind generation using statistical block. This block is able to combine inputs such as NWPs of the speed, direction, temperature etc. of various model levels, together with on-line measurements, such as wind power, speed, direction and others. With these models, a direct estimation of regional wind power from the input parameters is possible in a single step. This block can include one or several statistical linear and non-linear models of different types [17]. Some examples are so called "black-box" models, which include most of the artificial intelligence (AI) based models, such as ANNs and SVMs. Other types of models are the "grey-box" models, which learn from experience (from a dataset) and for which prior knowledge (such as diurnal variations) can be injected. The following types of statistical models have been proposed:

1) *Time Series Model*

Time series analysis is a method of forecasting which focuses on the past behavior of the dependent variable. Based on time series, there are further three types of models.

Persistence Model: This method uses the simple assumption that the wind speed at the time $t+x$ is the same as it was at time t. This is a very simple method and is used as a reference to evaluate the performance of the more advanced methods. This method is difficult to beat, especially on the short-term (1-6 hour) forecast. In fact, this simplified method is even more effective than a NWP model in some very short term predictions (several minutes to hours) [18]. The accuracy of this model degrades rapidly with increasing prediction lead time. In one of the variations of this method, one-day ahead prediction of wind speed using annual and seasonal trends has been proposed [19]. It has been pointed out that wind speed variations for a specific site may have some sort of common trend over specific periods of time. As a result, the wind speed in the present year can be predicted by the wind data from the previous years.

***ARIMA Model*:** The autoregressive integrated moving average model (ARIMA) has the advantage that its architecture, definition and parameter estimation procedures are very fast. This model normally comprises three components, which are autoregressive, integrated and moving average. ARIMA model is data independent.

Twelve research papers have been covered in this category. In [20], a modified ARIMA model to compute the 2.5 hour ahead forecasted growth/decline factor has been employed for the California Independent System Operator (ISO). The model's coefficients were adaptively adjusted to achieve the best accuracy and the bias self-compensation scheme. In [21], several statistical ARMA models have been employed to predict both wind speed and wind power output in hour-ahead markets. The authors in [22] predicted the hourly average wind speed up to 1~10 hours in advance by using ARMA models. In order to consider seasonal wind characteristic, the authors have adjusted a different model for each month. A methodology has been developed that used a Bayesian framework to model the wind speed time series as an AR process, where the Markov Chain Monte Carlo (MCMC) simulation is used to estimate the model parameters [23]. In [24], a method is based on a Markov-switching AR model with time-varying coefficients has been introduced for modelling short-term fluctuations. This method can also derive probability densities. The authors in [25] have also employed ARMA short term wind speed forecast based on historical wind speed data. An ARIMA model has also been used for time-series forecast and has been proved to be better than artificial neural network (ANN) model for short time-intervals to forecast (10 minutes, 1 hour, 2 hours and 4 hours) [26].

In [27], the relationship between the accuracy of the forecast and wind power variability has been established. Burg & Shanks algorithms have been used to determine the model coefficients. The deficiencies of the persistence methods in medium and long term have been found and a statistical method based on independent component analysis (ICA) and AR model has been presented [28]. In [17], ARIMA and ANN models from one to four hours ahead have been proposed. In [29], an

autoregressive conditional heteroscedastic (ARCH) model has been proposed. First, wind speed series has been decomposed and reconstructed into approximate series. Then ARIMA model was used to analyse each part, simultaneously considering the heteroscedasticity effect of the residual series.

Main characteristics of different time series models have been given in Table I and the forecasting performance comparison has been presented in Table II. It can be observed that many different types of preprocessing techniques have been employed by different researchers. This has been done to obtain more stable variance. Autocorrelation function (ACF) and partial autocorrelation function (PACF) are the preferred choice of researchers for model identification and estimation.

TABLE 1 MAIN CHARACTERISTICS OF TIME SERIES MODELS

Paper	Model type	Input variables	Series	Preprocessing employed	Model identification & validation
[22]	ARMA	Historical data	SS	Log transformation	ACF, PACF
[23]	ARMA	Historical dada	SS	Monte Carlo method	ACF, PACF
[26]	ARIMA & NN	Historical data	SS	Box Jenkins Methodology & Back Propagation	-
[27]	ARIMA & NN	Historical data	SS	Back propagation	-
[28]	ARMA	Historical data	SS	Wind pattern analysis	ACF, PACF
[17]	ARIMA-ARCH	Historical data	SS	Wavelet transform	ACF, PACF
[29]	ARIMA, SVM	Historical data	SS	Equal weight average method, covariance optimization, combination forecasts	-

SS-Single series, ACF - auto-correlation function, PACF - partial autocorrelation function

TABLE 2 FORECASTING PERFORMANCE COMPARISON OF TIME SERIES MODELS

Paper	Time horizon	Data used (days)	Predicted period	Output	Level of accuracy
[22]	6 hrs ahead	59 days	2 week	WPP	-
[23]	one hr ahead	365 days	1-10 hrs	WPP	RMSE 2-5%, 12-20%
[26]	1-4 hrs ahead	365 days	6 months	WPP	MAPE
[27]	10 min-4 hrs	-	10 mins	WPP	-
[28]	3 hrs ahead	One month	27 hrs	WPP	MAPE
[17]	-	264 data values	240 data values	WPP	MRE-8.72%
[29]	-	500 data values	-	WPP	MAE-18.5%, MAE-16.9%

WPP-wind power profile, RMSE-root mean square error, MAPE-mean absolute percentage error, MRE-mean relative error, MPE-mean positive error, MNE-mean negative error

The f-ARIMA model arises as a special case of ARIMA processes when the difference parameter 'd' assumes fractionally continuous values in the range (-0.5, 0.5). The advantage of f-ARIMA process from an ARIMA process is that the former is characterized by a slow decay in its ACF compared to the latter. This feature makes f-ARIMA models an attractive choice for data sets that exhibit long range correlations such as the wind speed [12]. The use of f-ARIMA models to model and forecast wind speeds on 24 h and 48 h horizon has been examined in case of North Dakota [12].

Data Mining Model: Data mining means extracting or "mining" knowledge from large amounts of data. It is a promising approach to develop prediction models for wind farm. This technique has a greater advantage, since the amount of data available in wind farms is huge and the possibility of making frequent updates in the prediction models is much easier, therefore resulting in improved prediction accuracy. The advantages and drawbacks of different data mining models used for wind power forecasting have been explained in [30]. These include linear models and non-linear models which comprise of NNs and SVMs.

Algorithms in four different domains, namely data mining, evolutionary computation, principal component analysis (PCA) and statistical process control have been applied for wind power forecasting [31]. A non-linear parametric model of the power curve of the wind farm was constructed with an evolutionary strategy algorithm. This curve was used to monitor the online performance of the wind farm. In [32], to improve the forecast precision, a forecasting method based on empirical mode decomposition (EMD) and wavelet decomposition combine with SVM has been proposed. The wind speed time series was decomposed into several intrinsic mode functions (IMF) and the trend term. To reduce the nature of non-stationary, the high frequency band was decomposed and reconstructed by wavelet transform (WT).

2) Artificial Neural Network (ANN) Model

The advantage of the ANNs is to learn the relationship between inputs and outputs by a non-statistical approach. These ANN-based methodologies do not require any predefined mathematical models. If same or similar patterns are met, this model comes up with a result with minimum errors. However, the accuracy of the prediction for these models drops significantly when the time horizon is extended. ANNs have been widely used as time series forecasters: most often these are feed-forward neural networks (FFNNs) which employ a sliding window over the input sequence. The standard NN method of performing time series prediction is to induce the function '*f*' using any feed forward function approximating NN architecture, such as a standard multilayer perceptron (MLP), radial basis function (RBF) architecture or a cascade correlation model [33], using a set of N-tuples as inputs and a single output as the target value of the network. This method is called the sliding window technique as the N-tuple input slides over the full training set [33-34]. Two important issues must be addressed in such systems: the frequency with which data should be sampled and the number of data points which should be used in the input representation. The available NN models are: (i) multilayer feed forward neural network (FFNN), (ii) genetic neural network (GNN), and (iii) recurrent neural network (RNN).

Fourteen research papers have been covered in this category. In [5], a recurrent higher-order neural network (RHONN) model has been developed for wind power forecasting in a wind park and can be used to predict wind speed or power in time scales from a few seconds to 3 hours ahead. The optimal architecture of the model was selected based on the cross validation approach and was solved using the non-linear simplex method. In [35], a methodology synthesizing both ANN technology and the linear regression has been introduced, where ANN was used to handle short-term patterns and the long-term trend information is provided by a trend identification module, which performs the first order linear regression. The authors in [36] introduced a methodology for assessing the risk of short-term wind power forecasts by using the ANN, historical predicted meteorological parameters and meteorological risk index (MRI) and production risk index (PRI). The authors in [37] proposed a statistical forecasting system by using a combination of statistical forecasting equations for 1~48h ahead wind power. The combination coefficients for each model are time-varying, which is similar to non-parametric models. The authors in [38] also utilized ANN to predict day-ahead wind power in Germany. For training, measured power data were used to learn physical coherence of wind speed and wind power output. The advantage of ANN application is that it can easily use additional meteorological data, such as air pressure or temperature, and power curves of individual plants to improve the accuracy of the forecasts.

An ANN based model that requires as input past power measurements and meteorological forecasts of wind speed and direction interpolated at the site of the wind farm has been presented [3]. The development of an ANN based wind power and its confidence interval (CI) forecast and the integration of wind forecast results into unit commitment (UC) scheduling has been performed in [39]. Short term wind speed forecasting has been done utilizing ANN in conjunction with Markov Chain (MC) approach [40]. ANN predicted short term values and the results have been modified according to the long term patterns applying MC. For verification purposes, the integrated proposed method has been compared with ANN.

The GNN technique for wind speed and power generation prediction has been introduced in [41]. Firstly, 3 hours wind speed was predicted by means of NN with measured wind speed data of latest 24 hours and then the wind power generation was forecasted based on the standard power curve. In [42], the forecasting model based on multi-agent technology, given prediction algorithm module flow, has been used. According to the

characteristics of self-learning agent, the authors made use of all interactivities of agent and modified the model of BPNN constantly to make predictions more accurately. The authors in [43], utilized the [4-8-1] FFNN to estimate wind power. The four inputs include measured data for wind velocities and directions from two meteorological towers. The proposed ANN was used to estimate the wind power generation directly based on the measured wind velocity and direction without manufacture's power curve. In [44], FFNN and RNN have been employed to forecast daily and monthly wind speed time series in India. The results show that the NN perform better than the ARIMA models. In [45], a method based on FFNN has been utilized to predict the average hourly wind speed. The input selection was determined on the basis of correlation coefficients between previous wind speed observations.

The authors in [4] deal with the 72 hour ahead forecasting for wind speed and power based on meteorological information. Three types of local RNN are employed as forecasting models and a method to combine time series approaches and atmospheric modeling simultaneously has been proposed.

3) Grey Model

Grey models predict the future values of a time series based only on a set of the most recent data depending on the window size of the predictor. It is assumed that all data values to be used in grey models are positive and the sampling frequency of the time series is fixed. The main task of the grey system theory is to extract realistic governing laws of the system using available data. This process is known as the generation of the grey sequence [46]. A technique for wind speed forecasting based on GM (1, 1) has been given in [47]. The results from the forecasting model have been used as an input to the power curve model for a 600-kW variable-speed wind turbine to predict the output power. The results obtained from the GM (1, 1) have been compared with the persistence model. In [48], the accuracies of different GMs such as GM (1, 1), grey verhulst model, modified GM using Fourier series have been investigated. The GM combined with MC model has been used in [49].

4) Fuzzy Logic Model

Fuzzy logic is a research area based on the principles of approximate reasoning. It uses soft linguistic variables (e.g. small, medium, and large) and a continuous range of membership values in the interval [0, 1], thus making a deviation from the classical sets [7]. Fuzzy models are employed in cases where a system is difficult to model exactly or when ambiguity and vagueness is encountered in the problem formulation. The authors in [50] have presented a fuzzy expert system that forecasts the wind speed and generated electrical power. The forecast horizon has been considered from some minutes up to several hours ahead. After tuning, the system can make reliable wind speed forecasts in less than a second.

Hybrid Model

Hybrid model is based on a combination of the physical and statistical models [51]. The object of this model is to benefit from the advantages of each model and obtain a globally optimal forecasting performance. The performance of wind power forecasts and the forecast accuracy depends on the availability of good NWP forecasts, the complexity of the terrain, and the availability of real-time weather and power plant data. Three types of combinations were utilized to predict wind power: (i) a combination of physical and statistical approaches (e.g. Zephyr model [52]), and (ii) a combination of models for the short-term (0 to 6 hr) and for the medium-term (0 to 48 hr), (iii) the combination of alternative statistical models. One example of that is the Spanish Sipreólico [39]. The combination is achieved through the use of the horizon as a criterion. The model that best suits each horizon is identified off-line or by a selection process based on the recent performance of each individual model.

Fours papers have been covered in this category. In [20], the authors indicated the necessity to involve forecasted weather parameters and unit status information into the model. They highlighted that the use of energy (MWh) instead of power (MW) as a forecasted parameter makes wind generation more predictable. In [53], the application of hybrid intelligent systems for short term wind power forecasting has been discussed. In [11], a hybrid model for forecasting wind speed based on the combination of WT and NN has been proposed. The proposed hybrid model to forecast wind speed is a combination of loose and compact wavelet NN (CWNN). By using this model, wind speed signal has been decomposed with WT and reconstructed to get each scale's sub-series. Then the subseries were predicted by CWNN. In [54], a short-term wind speed forecasting method based on ARIMA and least square support vector machine (LS-SVM) has been proposed. The weights

have been calculated by the two methods, equal weighted average method and covariance optimization combination forecast. Results show that the forecast accuracy from different methods has been diverse.

Another class of hybrid models combining ANNs and fuzzy logic have also been proposed. Four research papers have been covered in this category. A model, which uses on-line SCADA measurements as well as NWP as input, to predict wind power has been proposed [55]. The prediction system integrates models based on adaptive fuzzy-NN configured either for short-term (1-10 hours) or long term (1-48 hours) forecasting. The authors in [8] have introduced an adaptive neuron-fuzzy inference system (ANFIS) to forecast wind vector 2.5 minutes ahead, which takes both speed and direction into account. An ANFIS uses a hybrid learning algorithm that combines the least-square estimator and the gradient descent method. The need for accurate short term wind power forecasting has highlighted with particular reference to the five minute dispatch interval for the proposed Australian wind energy forecasting system [56]. Results show that ANFIS models can be a useful tool for short term wind power forecasting providing a performance improvement over the industry standard "persistence" approach. A statistical model based on a hybrid computational intelligence (CI) technique that merging NN and fuzzy logic for wind power forecasting has been presented [57].

Discussion on Key Issues

To define the objective or purpose of a wind energy forecast is the first step in designing a wind energy forecasting system. The most obvious objective is the prediction horizon from the present time and the frequency of the predictions (*e.g.* hours). Wind energy forecasting for a power system may have multiple objective, which may be met by different forecasting methods. To achieve the objective, various methodology issues require discussion. The issue related to wind forecasting are given as:

- *Characterising the uncertainty of a predicted inputs::* Power systems require knowledge of the forecasted wind energy uncertainty so they can prepare backup precautions if necessary. The following uncertainties need to be considered:

  Error in initial conditions, including the measured wind farm energy outputs, other measured weather parameters at various locations and the mesoscale weather data obtained for the NWP simulation.

  Predictability of the atmospheric behaviours - some situations are more stable and predictable than others. Examples of less predictable situations include storms, fronts.

  More complex the terrain at the wind farm, the greater the lokcalised wind turbulence and this is harder to model.

  Accuracy of power curve for the wind turbine, which defines the conversion of wind speed to wind power. The power curve also changes over time influenced by material fatigue and natural incidents such as accumulation of dirt on the blades.

  Wind generator failure caused by a number of design or maintenance based factors.

- *Predicting extreme events:* Observations of wind farm behaviour have shown that large swings in the power output can occur, due to sudden changes in the wind resource or wind speeds exceeding the cut off level causing wind farm shut down. Predicting the level and timing of these events is of most concern to all electricity market participants and power system operator. Another possible extreme event is using weather pattern recognition.

- *Verification:* Finally, a wind power forecasts needs verification. This depends on the objectives. Common verification criteria are level errors or phase errors by comparing the actual forecasts against the observed wind farm output. Level errors are the most common way to assess any forecast and there are many standard methods such as root mean squared error (RMSE), mean absolute error (MAE) and R-square statistic.

Conclusion

Wind power forecasting serves as a significant tool to improve the efficiency and reliability of power systems, which has a large share of wind power. Long-term prediction models are powerful tools for operation management of the wind energy market and the short term prediction models can be helpful to the on-site management of the wind farm. Due to differences in the existing applications (flat, complex terrain, offshore), it is difficult to compare prediction systems based on available results. The ultimate goal of wind power forecasting is to enhance the prediction accuracy and develop prediction models which would become a basis for predictive control aimed at optimizing the wind turbine control settings to maximize the power captured from the wind thus transforming the wind farm into a wind power plant.

From this, it is clear that a requirement for accurate wind forecasting in order that wind power can be integrated into the scheduling and dispatch decisions of the power system operators. Moreover, the restructuring and deregulation of the electricity industry taking place throughout the world will increase the importance of wind power forecasting to system operators and traders. This paper has reviewed the forecasting techniques that were applied to the wind speed and power. A constant improvement in these technologies is at present under way.

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